Factor Analysis via SAS

Good cite:

Larry Hatcher and Edward Stepanski, "Principal Component Analysis" (Ch. 14) in A Step-by-Step Approach to Using the SAS System for Univariate and Multivariate Statistics

Factor Analysis:
Purposes

1) Revealing patterns of inter-relationships
2) Detecting clusters of strongly correlated variables
3) Reducing large number of variables to smaller number of factors***

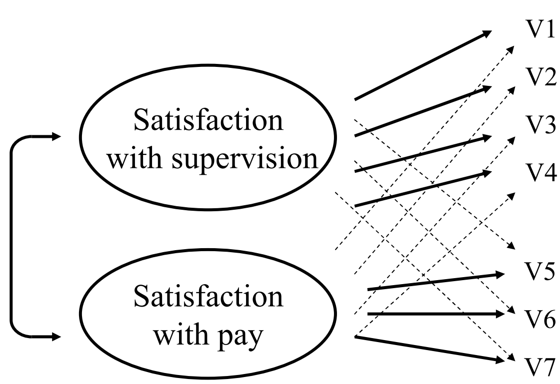
   (Way to handle multicollearity)

   ***We'll focus on (3)—scale construction

Factor Analysis

- Incorporate different variables to measure an underlying dimension
- Assumes an underlying causal structure

Factor Analysis



e.g., V1 = "My supervisor treats me with consideration"

V5 = "My pay is fair"

Source: Hatcher & Stepanski, p. 457

Factor Analysis:
Basic principle

- Start with large number of variables
- Find minimum number of underlying factors (principal components) that together account for the pattern of intercorrelations among observed variables
- ***Note***: variables must be coded in similar ways (high = high)

Factor Analysis:
properties of principal components

- Component = linear combination
- Orthogonal to each other
- 1^{st} principal component = largest variance of any linear function of original variables
- 2^{nd} principal component = second largest of remaining variance

Eigenvalues

"Characteristic root of the matrix"

- Used to calculate variance of the ***factors***
- Largest eigenvalue represents amount of variance in data explained by 1st factor
- Each factor has one eigenvalue
- Keep factors with eigenvalues > 1.0
- Wide variation in eigenvalues = severe multicollinearity

Eigenvectors

- AKA "***factor loadings***" (or, factor structure)
- Coefficients for linear transformation of the standardized variables
- Use to interpret structure of variables
- Used to compute correlations between original variables and new factor variables
- SAS: coefficients in factor pattern matrix and rotated factor pattern matrix

Eigenvectors (cont.)

Each observed variable viewed as determined by underlying factors:

e.g., Var1 = weight*F1 + weight*F2 + weight*F3 . . . + weight*μ

Interpretation: largest weight = most important determinant

Eigenvectors (example)

Var1 = .889F1 + .078F2 + .032F3 + dμ

- $(\text{weight})^2$ = proportion of variance in variable accounted for by factor
- $(.889)^2$ = 79% of variance in Var1 explained by F1

Eigenvectors (example)

h^2 (communality of variable):

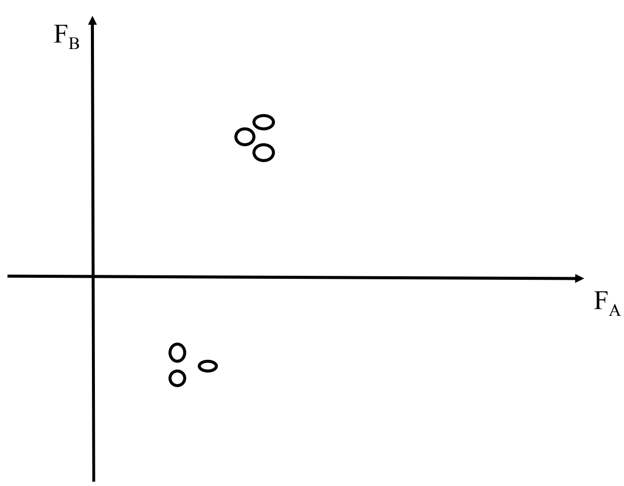
$h^2 = (.889)^2 + (.078)^2 + (.032)^2$

h^2 = 79.7% of variance in Var1 explained by F1 to F3

$1-h^2$ = proportion left unexplained by F1 to F3

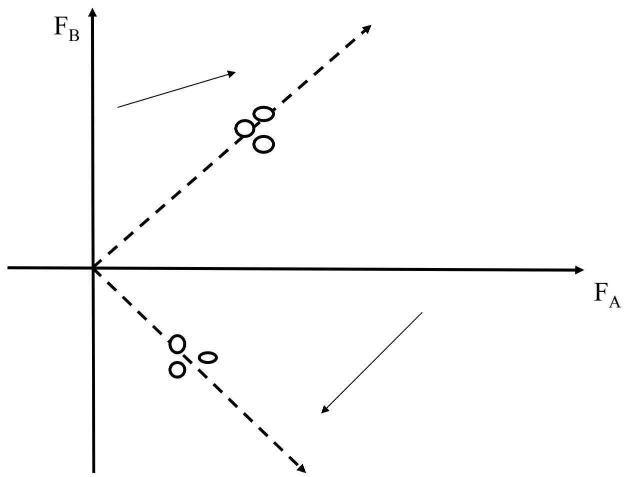
$\sqrt{1-h^2} = d$ (weight for residual term)

Rotation



Rotation:

(Varimax: maximizes contrast)



Evaluate

- Factors are orthogonal, whether rotated or not
- Rotation makes clustering more obvious
- We'll use "Varimax Rotation": maximizes contrast between factors
- Evaluate loadings: criteria = .4 or .5

Evaluate

Principal component analysis ≠ factor analysis:

•Factor analysis assumes an underlying causal structure

•Principal component analysis makes no assumption of underlying causal model